Intelligent Traffic Management using IoT and Machine Learning

Reem Atassi[1,*], Aditi Sharma[2,3]

[1]Faculty of Computer Information System, Higher Colleges of Technology, UAE

[2]IEEE Senior Member, Parul University, Vadodara, India

[3]Department of Computer Science and Engineering, Parul Institute of Technology.

Emails: ratassi@hct.ac.ae; aditi11121986@gmail.com

Abstract

The continuous improvements on the Internet of Things (IoTs) and machine learning (ML) make them the key enabling technologies for intelligent traffic management (ITM). The ability to accurately predict network traffic has been demonstrated as crucial for effective network management and strategic planning. Proactive management of future congestion incidents requires access to reliable long-term forecasting models. Conventional prediction methods often fail to completely capture the spatiotemporal features of the traffic flows because of the complexity of the interdependence between the flows. To this end, we proposed to improve the management of traffic with a novel framework for the predictive modeling of traffic flows. The proposed formwork introduces an improved graph network to capture the positional information in traffic follows. It is also capable of precisely capturing temporal dynamics using an improved bidirectional learning module. An attention mechanism is presented to capture the interactions among spatial and temporal patterns to further empower the predictive power of the model. Proof-of-concept experimentations are conducted on the PeMSD7 dataset, and the results (MAE: 0.197, MSE: 0.13, RMSE: 0.36, R^2: 0.89) demonstrate the efficiency of our model over the state-of-the-art.

Keywords: Intelligent Traffic management systems; IoT, Intelligent Systems; Machine learning

1. Introduction

Intelligent traffic management (ITM)is an emerging field that utilizes advanced technologies and data analysis to improve the efficiency, safety, and sustainability of transportation systems. Managing traffic effectively and reliably is essential to the success of the Smart Transportation industry, which facilitates the timely and secure transport of people and commodities. With real-time data on traffic conditions, the IoT paves the way for improved decision-making and more efficient control of traffic flow, playing a crucial role in enhancing traffic management in transportation [1]. Devices connected to the Internet of Things can gather information about variables including traffic volumes, travel times, and vehicle speeds and locations. Algorithms designed specifically for machine learning can be used to this data to discover regularities, spot outliers, and foresee how traffic will behave in the future. The data can help with traffic

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management, congestion alleviation, and security. With the use of the Internet of Things (IoT), transportation agencies may provide passengers with a variety of services, including automatic issue management, tailored route planning, and real-time traffic reports [2].

ITM systems can help to make transportation networks more efficient, sustainable, and safe, by utilizing real-time data from traffic sensors, cameras, and other sources to make data-driven decisions. One of the key benefits of ITM is its ability to reduce traffic congestion. ITM systems can analyze real-time traffic data to identify bottlenecks and adjust traffic flow accordingly. This can help to reduce travel times, increase mobility, and improve the overall performance of transportation networks [3]. By using real-time data to monitor traffic conditions, ITM systems can help to identify potential hazards and reduce the risk of accidents. For example, ITM systems can use real-time data to adjust traffic signals, warn drivers of upcoming hazards, and provide real-time information about road conditions [4]. In addition to reducing congestion and improving safety, ITM can also help to promote sustainable transportation options. ITM systems can prioritize public transit, biking, and walking over private vehicles, by adjusting traffic signals, providing real-time information about transit schedules, and encouraging alternative modes of transportation [5].

Accurate prediction of traffic flow has been considered an important requirement to improve the functionality of ITM systems. machine learning (ML) has been demonstrating great success in different prediction tasks. Recurrent networks, convolutional networks, and graph networks are all examples of ML methods applied for traffic modeling. However, the complexity and interdependency of traffic flow make this prediction task an open challenge that is worth investigating [6].

This paper introduces a novel ML model for predictive modeling of the traffic flow captured with IoT sensors aiming to improve the ITM system in smart cities. The proposed model applies and improved graph convolutions to capture spatial characteristics of traffic flows by representing them in form of graphs. Simultaneously, we learn the temporal dynamics of traffic flows using bidirectional recurrent networks. Then, both temporal features and spatial ones are combined and tuned to generate an accurate prediction of traffic flows.

This paper is organized as follows: this section introduces the importance of traffic management in IoT and its application in transportation. Section 2 reviews the literature on practical applications of machine learning techniques for traffic management in IoT. Section 3 debates the methodology of the proposed framework. Section 4 discusses the experiments of this work and related settings. Section 5 summarizes the main findings of this paper**.**

2. Related Work

These issues may be remedied with the continued advance in ML, the researcher exerts many efforts to develop intelligent machine learning solutions for improving traffic management. For example, the work [1] surveyed the application of ML algorithms (e.g., Convolutional Neural Network (CNN), K-Nearest Neighbor (KNN)) for developing ITM and presented a methodology of these methods that consisted of some stages according to some aspects such as data collection. The work also highlighted the challenges facing ITM research, such as the need for more accurate and real-time traffic data, the integration of multiple data sources, and the development of more sophisticated ML algorithms that can handle the complexity of real-world traffic systems. The work [2] developed a recommendation system based on a human-in-the-loop parallel learning paradigm, which consisted of three components namely data preprocessing, feature extraction, and a recommendation engine. The system was evaluated on real-world traffic data from Hangzhou, China. The work [3] introduced an agent-based traffic recommendation system that utilizes reinforcement learning to develop urban traffic management strategies. The proposed system consists of two components: a traffic simulator and a reinforcement learning-based recommendation engine. The traffic simulator generates synthetic traffic data based on real-world traffic patterns, and the recommendation engine used a

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Q-learning algorithm to learn and revise traffic management strategies based on the simulated data. The work [4] presented a fuzzy logic-based traffic management system for high-speed networks, which is composed of three components: a fuzzy traffic model, a fuzzy controller, and a user interface. The fuzzy traffic model was applied to model traffic flow and predict traffic conditions. The fuzzy controller was designed to generate traffic control commands based on the traffic model and the current traffic conditions. The work [5] developed a parallel transportation system (PTS) that integrates various IoT technologies to enable smart urban traffic control and management. The proposed PTS was composed of three system layers: the perception layer, the decision-making layer, and the control layer. The perception layer was designed to collect and processes real-time traffic data using various IoT technologies, such as sensors, cameras, and GPS. The decision-making layer applied ML algorithms to analyze the data and make intelligent traffic control decisions. The control layer implements the decisions by controlling traffic signals, route guidance systems, and other transportation infrastructure. The reported results showed that the system can significantly reduce travel time, vehicle delay, and fuel consumption compared to traditional traffic control methods. The system can also adapt to changing traffic conditions and dynamically adjust its control strategies. The work [6] proposed an online incremental ML platform for big data driven ITM, which includes an offline module and the online module to respectively trains ML models using historical traffic data and updates them in real-time using incremental learning algorithms and real-time traffic data. The work [7] developed a thresholds-based image extraction scheme for ITM in a big data environment, in which a Faster Region Convolutional Neural Network (RCNN) was proposed to slice a traffic image into multiple areas with dissimilar rank stages; and image extraction structures with many thresholds were proposed depending on liberal undisclosed image sharing methods to learn images containing primary traffic info, like human faces, reg number, whereby the area with advanced reputation level needs high threshold for abstraction. The work [8] presented T-GCN (Temporal Graph Convolutional Network) as a type of neural network that is particularly designed for traffic prediction tasks based on temporal and spatial dependencies of traffic data by incorporating both time-series and graph-based information. The T-GCN consisted of several layers of graph convolutional operations that process the traffic data at different levels of abstraction-GCN also incorporates a novel attention mechanism that helps the model focus on the most relevant information at each time step. The attention mechanism calculates a weight for each node in the graph based on its relevance to the prediction task, allowing the model to selectively emphasize important nodes and ignore irrelevant ones. The work [9] addressed traffic speed prediction based on a spatial-temporal tensor graph convolutional network (ST-TGCN) that was designed to capture the spatial and temporal dependencies of traffic speed data by incorporating both time-based and graph-based information. The model uses a tensor representation to encode the spatiotemporal data, where the first two dimensions represent the spatial locations, and the third dimension represents the time. The model also incorporates a multi-scale convolutional architecture to capture both short-term and long-term temporal patterns in the traffic data. Additionally, the model uses a novel loss function that combines both mean absolute error (MAE) and mean squared error (MSE) to account for both the magnitude and direction of the prediction errors. The work [10] developed a graph-based system for handling spatial dependency between infrastructures of a similar network, in which the traffic network was designated as a graph, where the Breadth First Search was applied to learn the local neighbors of each road. This work applied Pearson correlation-coefficient indicator to the nominated graph nodes for an agreed number of neighbors to assess the ability of the model to predict road traffics. The work [11] proposed a new approach for forecasting traffic situations using a spatial-temporal graph model, named STGSA, that handles the complex dependencies and interactions between different road segments in a road network. The model used a graph-

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based representation of the road network, where each node represents a road segment and edges represent the connections between them. The model can learn the spatiotemporal patterns of the traffic flow by analyzing the data from multiple sources, such as GPS data, traffic sensors, and social media. STGSA used a synchronous aggregation mechanism to combine the information from different nodes in the graph. The STGSA applied a recurrent neural network (RNN) to learn the temporal patterns of traffic flow, and a graph convolutional neural network (GCN) to learn the spatial dependencies between different road segments. The work [12] designed a graph model to handle the complex dependencies and interactions between different road segments in a road network by representing the road network as a spatial-temporal graph. The model was based on a hierarchical architecture that captures both local and global dependencies between different road segments. The authors argue that the hierarchical approach is necessary to accurately predict traffic flow, as the traffic patterns may vary at different levels of granularity. The work [13] developed a multi-stream feature combination method to excerpt and participate ridiculous features from traffic data and leverage data-based adjacency rather than distance matrix to build graphs. Spearman rank correlation factor was computed between screen positions to get the initial adjacency and weak it during training. multi-stream feature fusion block (MFFB) block was applied to comprise graph convolutions, GRU, and a fully connected network, which was exploited to acquire spatial, time-based, and other representations, correspondingly. Then, these features were combined using the soft-attention method. The work [14] proposed a graph representational learning model to predict traffic speed, in which road segments are represented by nodes and the link between them is represented by edges. The model was proposed based on a combination between graph convolutions and LSTM to learn the spatial dependencies and temporal patterns of traffic flow, respectively. The work [15] developed a graph network based on the integration of recurrent network and graph convolution that enable learning and optimized graph representation through latent association among the road sections from the traffic information.

3. Proposed Work the Machine Learning model for IoT-based Traffic Management System

This section discusses the methodology of the proposed framework for the predictive modeling of traffic flows from IoT-based ITM systems. the architecture of the proposed framework is depicted in figure 1. As shown, the proposed model consists of two main building blocks one to capture and learn spatial information and the other one learns the temporal characteristic of traffic flows. The following sections provide a detailed description of each part of our model.

A. Spatial Module

This part of the network seeks to learn the spatial patterns in traffic flows. This is achieved by proposing an improved graph convolutional model that is composed of a stack of many spatial layers, in which each layer comprises one graph convolution connected densely. The production of the spatial module is the chain of compositional layers, where the kth layer's output is expressed as follows:

$$H^k = f\left(W^k \odot P^k X\right) s.t.: P = D^{-1}A \tag{1}$$

where $f(\cdot)$ denotes the layer's activation and $P \in \mathbb{R}^{N\times N}$ denote probability function, and W signifiesweights matrices.Successively, the output is modified to compute a totality at each layer as follows:

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$$Z = \sum_{k=0}^{K-1} f(P^k X W^k) \quad (2)$$

B. Temporal Module

Literature studies have agreed that the temporal dynamics of traffic flows are essential information for improving the predictivity of ML algorithms. Thus, the building of our model should consider learning such features. To achieve that, bidirectional Gated Recurrent Units (GRUs) are applied to extract and learn temporal dependencies in traffic flows. The primary idea behind using GRUs is to make use of gating mechanisms to selectively update and reset the network's memory, which empowers the network to capture long-term dependencies in the data. GRU is composed of two gates that control the flow of information through the network namely the update gate and reset gate. The update gate, Z_t, controls how much of the previous hidden state should be retained, while the reset gate, r_t , determines how much of the new input should be added to the new hidden state, h_{t-1}.In mathematical terms, the computation of GRU gates can be expressed as follows:

$$Z_t = \sigma(W^z x_t + V^z h_{t-1} + b_z) \quad (3)$$
$$r_t = \sigma(W^r x_t + V^r h_{t-1} + b_r) \quad (4)$$

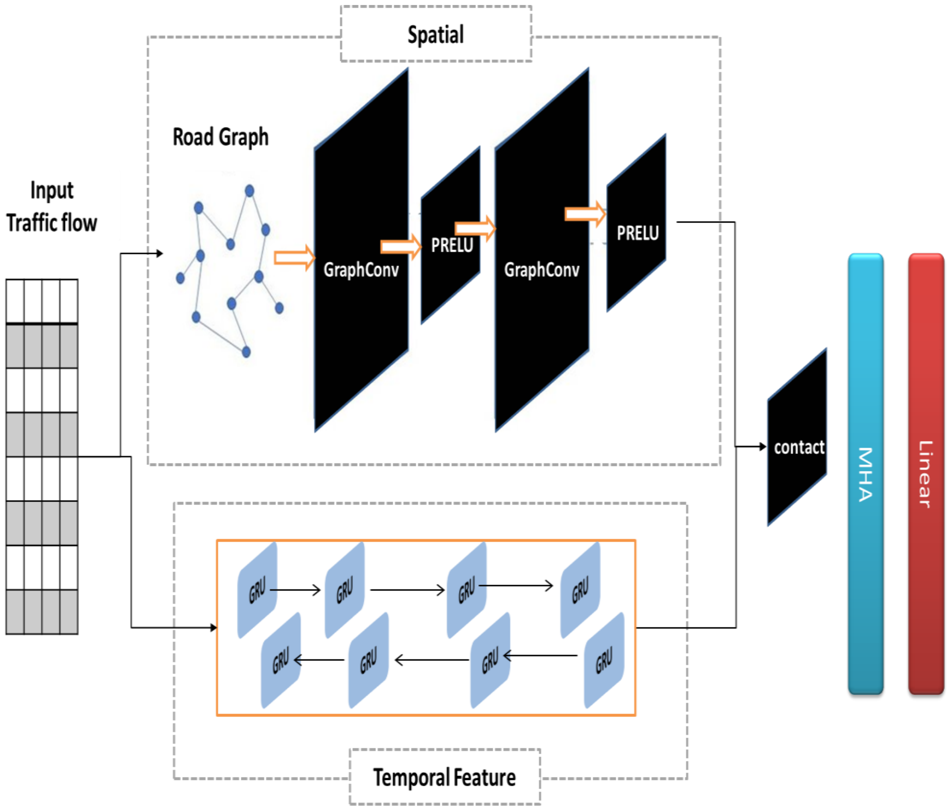

Figure 1: visualization of the architecture of the proposed framework

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The hidden state, h_t, and candidate state, $\tilde{h}_t$ are followingly computed as follows:

$$h_t = (1 - z_t) \otimes h_{t-1} + z_t \otimes \tilde{h}_t \tag{5}$$

$$\tilde{h}_t = \tanh(W^c x_t + V^c(r_t \otimes h_{t-1})) \tag{6}$$

In the above formula, the W^z, W^r, and W^c denote the weights of the inputs, while V_z, V_r, and V_c denote the gating parameters. The b denotes the bias vectors.

Further, the design of the bidirectional GRU module is composed of two GRU layers one processing the information in the forward direction and the other in the backward direction. By the end of the bidirectional GRU module, we obtain a combinatorial hidden state by summing the value of hidden states of both forward and backward layers. This can be expressed as follow:

$$\overrightarrow{h_t} = \overrightarrow{GRU}(X_t, \overrightarrow{h_{t-1}}) \tag{7}$$
$$\overleftarrow{h_t} = \overleftarrow{GRU}(X_t, \overleftarrow{h_{t-1}}) \tag{8}$$
$$h_t = \overrightarrow{h_t} \oplus \overleftarrow{h_t} \tag{9}$$

A. Tuning module

The output of both temporal and spatial modules is combined in this stage of the model, in which we seek to improve the interaction between both temporal and spatial representations of the traffic flow using multi-head self-attention (MHA) [16-18]. The computation of MHA can be expressed as follows:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{10}$$

$$\text{head}_i = \text{Attention}\left(QW_i^Q, KW_i^K, VW_i^V\right) \tag{11}$$

$$\text{MHA} = \text{Concat}(\text{head}_1, \dots, \text{head}_h) \tag{12}$$

In the above formula, the $\sqrt{d_k}$ represent regularity factor for query $Q \in \mathbb{R}^{n \times d_k}$, value $V \in \mathbb{R}^{m \times d_v}$, and key $K \in \mathbb{R}^{m \times d_k}$.

In the nutshell, the proposed ITM model can effectively and concurrently learn complicated spatial representations and temporal representations within traffic flows. An improved residual graph convolution model oversees learning the first type of representation, while a bidirectional recurrent network is developed to learn the later representation. Multi-head attention is presented to improve the interaction among temporal and spatial patterns and improve the final traffic prediction performance.

B. Training

To train the proposed model, Huber loss is applied as our objective function since its less sensitive to outliers compared to MSE and MAE. The Huber loss computes as follows:

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$$\text{Huber}(x) = \begin{cases} \frac{1}{2}x^2 & \text{for } |x| \le \delta, \\ \delta|x| - \frac{1}{2}\delta^2 & \text{otherwise.} \end{cases} \quad (13)$$

where δ symbolizes an adaptable parameter that panels where the transformation happens.

4. Results and Discussion

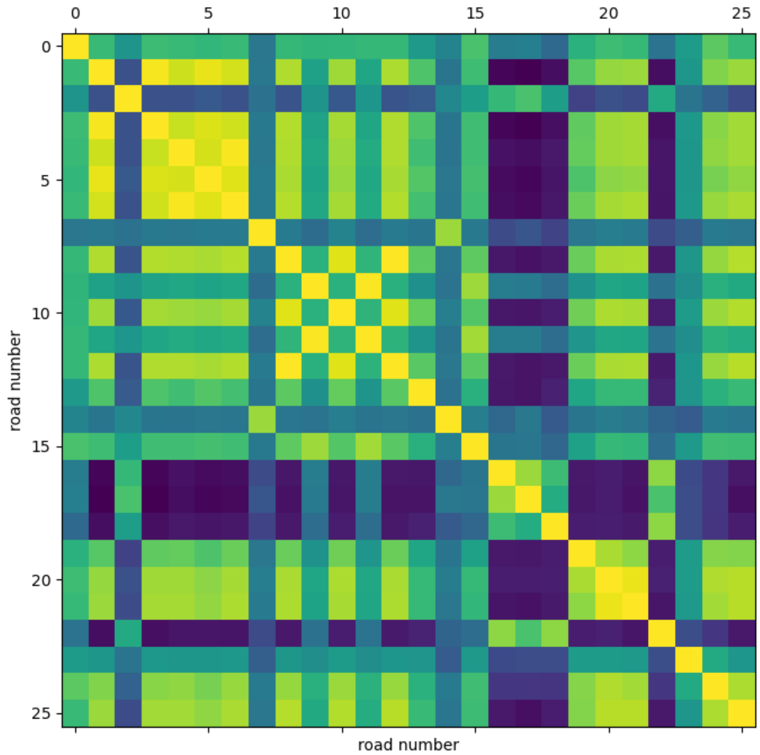

Figure 2: visualization of the heat maps of adjacency matrix

A. The performance

To evaluate the feasibility of the proposed model experimentally, the PeMSD7 traffic dataset was used in our experiments. It contains traffic information in District 7 of California comprising the speed measurements form 39, 000 sensors with 5-minute or/and 30 seconds resolution on the time interval between May2012 and June 2012.

The typical time interval is set to 5 minutes in our experiments leading nodes of the road graph encompass a total of 288 samples every day. The missed data points were fulfilled with linear interpolation. Besides, the Z-Score method was applied to normalize the input elements. We calculate the adjacency matrix for the road graph according to the distances, d_{ij} ,between pairs of traffic stations. The weight of the edge,w_{ij}, in the adjacency matrix Wexpressed as follows:

$$w_{ij} = \begin{cases} \exp\left(-\frac{d_{ij}^2}{\sigma^2}\right), & i \neq j \text{ and } \exp\left(-\frac{d_{ij}^2}{\sigma^2}\right) \geq \epsilon \\ 0, & \text{otherwise.} \end{cases} \quad (14)$$

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The $\sigma^2 = 10$and $\epsilon = 0.5$ represent thresholds to regulate the adjacency distribution and sparsity of matrix W. Figure 2 showsa heatmap of the adjacency matrix from PeMSD7.The predictivity performance was evaluated using four metrics that estimate the difference between the model's predictions,$\hat{Y}$, andreal traffic information$Y$. These metrics can be expressed as follows:

$$\text{Mean Square Erro(MSE)} = \frac{1}{n}\sum_{i=1}^{n} (Y_t - \hat{Y}_t)^2 \tag{15}$$

$$\text{Root MSE(RMSE)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (Y_t - \hat{Y}_t)^2} \tag{16}$$

$$\text{Mean Absolute Error (MAE)} = \frac{1}{n}\sum_{i=1}^{n} |Y_t - \hat{Y}_t| \tag{17}$$

$$R^2 = 1 - \frac{\sum_{i=1} (Y_t - \hat{Y}_t)^2}{\sum_{i=1} (Y_t - \bar{Y})^2} \tag{18}$$

To understand the competitive advantage of the proposed method, Table 1 presents the numerical results obtained from experimental comparisons between the proposed methods and the competing methods (support vector regressor (SVR), graph attention network (GAT), full connected LSTM(FC_LSTM), Foreword Neural Network (FNN))in the literature. Notably, the proposed system can achieve powerful predictive performance overcoming the competing methods. This can be attributed to the ability of our model to effectively capture the spatial and temporal features from traffic flow and the relation between them, which empowers the predictive power of the network.

Table 1: comparison between prediction performance of different ML methods on PeMSD7

	MAE	MSE	RMSE	R^2
ARIMA	0.499±0.022	0.350±0.072	0.592±0.07	0.667±0.001
SVR	0.491±0.098	0.321±0.003	0.567±0.028	0.704±0.077
FNN	0.459±0.061	0.286±0.017	0.535±0.008	0.753±0.086
FC-LSTM	0.433±0.037	0.207±0.009	0.455±0.033	0.757±0.049
GAT	0.364±0.002	0.206±0.082	0.453±0.034	0.764±0.039
T-GCN	0.267±0.074	0.171±0.013	0.414±0.054	0.828±0.001
STGCN	0.238±0.028	0.137±0.015	0.37±0.042	0.879±0.052
Proposed	0.197±0.006	0.130±0.022	0.36±0.038	0.89±0.053

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Moreover, to analyze the stability of our model during the training we plot the training curves in Figure 3. Notably, the proposed model maintains stable learning behavior during the training stage. The model can also achieve notable fast convergence under different loss functions. To further validate the predictive power of the proposed model, we visualize the model predictions against real data in Figure 4. The prediction curves notably demonstrate the model can precisely predict the traffics flow, which makes it a reliable tool for improving ITM tasks.

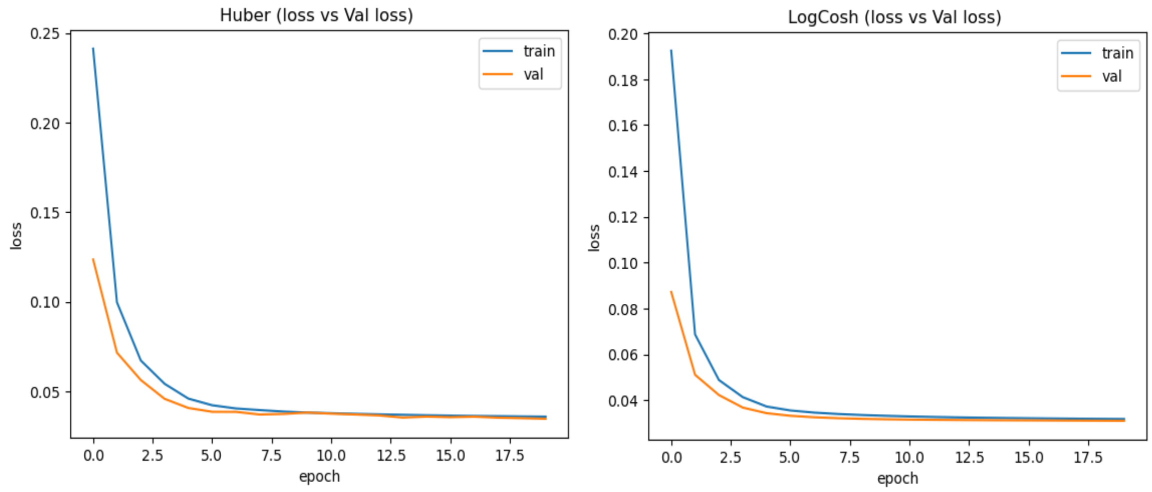

Figure 3: visualization of training curves of the proposed model under different loss functions

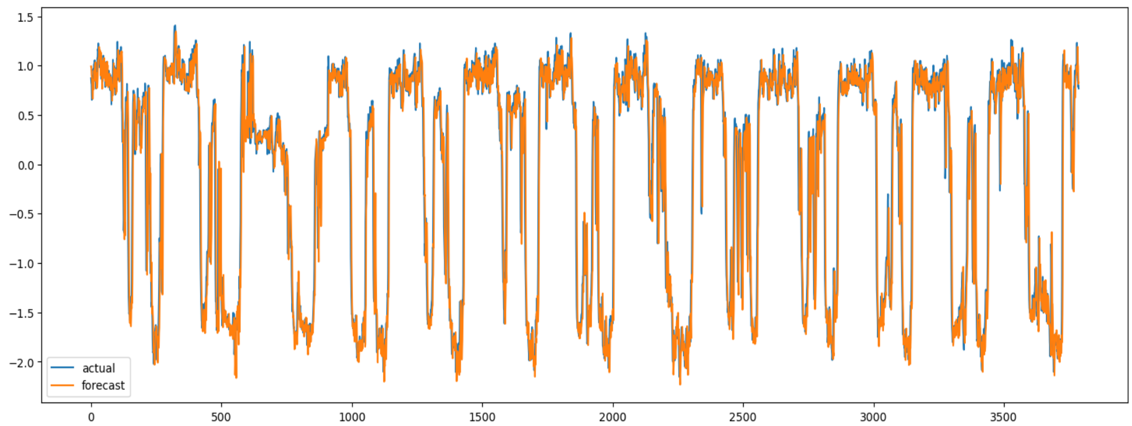

Figure 4: visualization of predictions of the proposed mode against actual traffic flow.

5. Future Scope and Conclusion

This research study presents a novel predictive modeling ML framework to forecast future traffic flows for improving the management of traffic in IoT environments. The temporal characteristics as well as the spatial information of traffics are captured as complementary sets

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for improved prediction. Then, the interaction between both patterns of information was modeled to further improve the predictive power of the proposed model. Experimental validations demonstrated the efficiency and competitiveness of the proposed method over cutting-edge approaches. The ability of our method to capture a complementary set of representation of traffic flows make its candidate tool to be deployed in real-world ITM system.

References

[1] Modi, Y., Teli, R., Mehta, A., Shah, K. and Shah, M., 2022. A comprehensive review on intelligent traffic management using machine learning algorithms. *Innovative infrastructure solutions*, *7*(1), p.128.

[2] J. Jin, H. Guo, J. Xu, X. Wang and F. -Y. Wang, "An End-to-End Recommendation System for Urban Traffic Controls and Management Under a Parallel Learning Framework," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 3, pp. 1616-1626, March 2021, doi: 10.1109/TITS.2020.2973736

[3] J. Jin *et al.*, "An Agent-Based Traffic Recommendation System: Revisiting and Revising Urban Traffic Management Strategies," in *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 52, no. 11, pp. 7289-7301, Nov. 2022, doi: 10.1109/TSMC.2022.3177027.

[4] J. Liu and O. W. W. Yang, "Using Fuzzy Logic Control to Provide Intelligent Traffic Management Service for High-Speed Networks," in *IEEE Transactions on Network and Service Management*, vol. 10, no. 2, pp. 148-161, June 2013, doi: 10.1109/TNSM.2013.043013.120264.

[5] F. Zhu, Y. Lv, Y. Chen, X. Wang, G. Xiong and F. -Y. Wang, "Parallel Transportation Systems: Toward IoT-Enabled Smart Urban Traffic Control and Management," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 10, pp. 4063-4071, Oct. 2020, doi: 10.1109/TITS.2019.2934991.

[6] D. Nallaperuma *et al.*, "Online Incremental Machine Learning Platform for Big Data-Driven Smart Traffic Management," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 12, pp. 4679-4690, Dec. 2019, doi: 10.1109/TITS.2019.2924883.

[7] Y. Liu, C. Yang and Q. Sun, "Thresholds Based Image Extraction Schemes in Big Data Environment in Intelligent Traffic Management," in *IEEE Transactions on Intelligent*

DOI: https://doi.org/10.54216/JISIoT.080201
Received: August 17, 2021 Accepted February 20, 2023

Transportation Systems, vol. 22, no. 7, pp. 3952-3960, July 2021, doi: 10.1109/TITS.2020.2994386.

[8] Lee, S., Kim, Y., Kahng, H., Lee, S.K., Chung, S., Cheong, T., Shin, K., Park, J. and Kim, S.B., 2020. Intelligent traffic control for autonomous vehicle systems based on machine learning. *Expert Systems with Applications*, *144*, p.113074.

[9] L. Zhao *et al*., "T-GCN: A Temporal Graph Convolutional Network for Traffic Prediction," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 9, pp. 3848-3858, Sept. 2020, doi: 10.1109/TITS.2019.2935152.

[10] X. Xu, T. Zhang, C. Xu, Z. Cui and J. Yang, "Spatial–Temporal Tensor Graph Convolutional Network for Traffic Speed Prediction," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 1, pp. 92-103, Jan. 2023, doi: 10.1109/TITS.2022.3215613.

[11] A. Salamanis, D. D. Kehagias, C. K. Filelis-Papadopoulos, D. Tzovaras and G. A. Gravvanis, "Managing Spatial Graph Dependencies in Large Volumes of Traffic Data for Travel-Time Prediction," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 6, pp. 1678-1687, June 2016, doi: 10.1109/TITS.2015.2488593.

[12] Z. Wei *et al*., "STGSA: A Novel Spatial-Temporal Graph Synchronous Aggregation Model for Traffic Prediction," in *IEEE/CAA Journal of Automatica Sinica*, vol. 10, no. 1, pp. 226-238, January 2023, doi: 10.1109/JAS.2023.123033.

[13] H. Wang, R. Zhang, X. Cheng and L. Yang, "Hierarchical Traffic Flow Prediction Based on Spatial-Temporal Graph Convolutional Network," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 9, pp. 16137-16147, Sept. 2022, doi: 10.1109/TITS.2022.3148105.

[14] Z. Li *et al*., "A Multi-Stream Feature Fusion Approach for Traffic Prediction," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 2, pp. 1456-1466, Feb. 2022, doi: 10.1109/TITS.2020.3026836.

[15] J. J. Q. Yu, C. Markos and S. Zhang, "Long-Term Urban Traffic Speed Prediction With Deep Learning on Graphs," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 7, pp. 7359-7370, July 2022, doi: 10.1109/TITS.2021.3069234.

DOI: https://doi.org/10.54216/JISIoT.080201
Received: August 17, 2021 Accepted February 20, 2023

[16] Moftah, H. M., & Mohamed, T. M. 2020. A Novel Fuzzy Bat Based Ambulance Detection and Traffic Counting Approach. Journal of Cybersecurity and Information Management, 1(2), 41-54. https://doi.org/10.54216/JCIM.010203.

[17] Abualkishik, A.Z., Almajed, R., & Thompson, W. 2021. Multi-attribute decision-making method for prioritizing autonomous vehicles in real-time traffic management: towards active sustainable transport. International Journal of Wireless and Ad Hoc Communication, 3(2), 91-101. https://doi.org/10.54216/IJWAC.030204

[18] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, Ł. and Polosukhin, I., 2017. Attention is all you need. *Advances in neural information processing systems*, *30*.

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